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Determinants of Credit Default Swap Spreads: A Four-Market Panel Data Analysis

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Abstract

This paper attempts to elucidate whether firm performance and macroeconomic conditions play a significant role in explaining credit default swap (CDS) spreads. Our panel dataset covers 112 reference entities in four markets (South Korea, Hong Kong, France, and Germany) for the period 2001-12. Overall, our results suggest that market value indicators (Tobin's Q, stock market returns, and the interest rate) appear to be more important than book value indicators (i.e., ROA, ROE, and the GDP growth rate) in determining CDS spreads. Moreover, Asian CDS markets are shown to be more sensitive to both GDP and stock market volatility, than the two European markets. Finally, the 2007-09 global financial crisis may have significantly affected the CDS market as a whole, but it generally did not affect the individual markets. These results are robust to various model specifications. This paper contributes to the understanding of CDS determinants at firm-, economy-, and market-level.

JEL classifications: G10, G15, G32

Keywords: credit default swaps, structural models, firm performance, macroeconomic conditions, financial crisis, GARCH volatility

1. Introduction

First introduced *circa* 1994 by JP Morgan, credit derivatives have substantially expanded over the past decade. Since their development, credit default swaps (CDSs) have attracted a wide range of users, from

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banks and other financial institutions to corporate and supranational bodies. According to Depository Trust and Clearing Corporation (DTCC) statistics, the gross notional amount of CDS trading was $25.9 trillion as of the year-end of 2011, and the net notional amount stood at $2.7 trillion. As their primary function, CDSs provide lenders with a form of protection against the occurrence of a credit event—borrower (reference entity) default. The formation of a CDS contract involves the following conventional setting: When a lender (the protection buyer) purchases a CDS from an insurance company or another financial institution (the protection seller), the loan becomes an asset that may be swapped for cash in the event of loan default. If no credit event occurs, the protection buyer makes premium payments until the contract matures; however, if a credit event occurs, then the protection seller pays the buyer for the loss, and the contractual relationship ends.

Undoubtedly, the key feature of a financial product is the "price", which is represented by the "spread" in the case of CDSs. In a CDS contract, the amount of the protection premium, which is the annual amount that the protection buyer must pay the protection seller over the length of the contract, can be calculated from the "CDS spread". As with any other insurance product, the CDS spread can be regarded as the price of risk. Any changes in factors that could alter the perceived level of risk will cause an adjustment in the CDS spread. Given the emerging significance of CDSs as a risk management product in financial markets over the past decade, further knowledge about the determinants of CDS spreads will certainly provide more insight into the probability of default and ensure that both financial regulators and risk managers better understand the use of CDS contracts. In actual fact, this remains the main motivation of our current research.

The present paper aims to further contribute to the understanding of CDS pricing by expanding the search for CDS determinants to a multi-level dimension. Fundamentally, we employ a structural model and examine factors at three levels: microeconomic (firm); macroeconomic (economy); and across four markets in two continents (market), that theoretically contain information about CDS spreads. To facilitate a comparative study, we select four international CDS markets from two continents – Asia and Europe. The vast majority of studies in CDS employ US dataset (e.g., Houweling & Vorst, 2005; Ericsson, Jacobs, & Oviedo, 2009; Zhang, Zhou & Zhu, 2009; Cao, Yu, & Zhong, 2010; Bai & Wu, 2011; Doshi, Ericsson, Jacobs, & Turnbull, 2013; Galil, Shapir, Amiram, & Ben-Zion, 2014), while researches on other markets are relatively limited (e.g., Monfort & Renne, 2014; Doshi, Jacobs, & Zurita, 2014). We purposely choose Hong Kong, South Korea, France, and Germany for our study due to two main reasons: 1) Hong Kong is a major Asian financial hub which provides important services in international finance, whereas some South Korean conglomerates such as Samsung, Hyundai play a significant role in the global economy. 2) France and Germany[1] are the two largest Euro-denominated CDS markets. With this approach, we aim to capture any region/market-specific variations—that is, we wish to examine whether our results are affected by a market's geographical location. The hypothesized outcome is that, either: (i) no differences exist, i.e., all CDS markets are the same (homogeneous), or (ii) due to geographic and cultural reasons, the two Asian markets are similar, whereas the two European markets are alike; in other words, we can classify the four markets into either the Asian market group or the European market group.

The present paper has three distinctive features: first, as microeconomic variables, we include both market value and book value firm performance measures; second, we simultaneously examine both levels of and changes in CDS spreads; and third, we conduct two separate studies of our data by initially aggregating the CDS data from the four markets, and is then followed by a comparative analysis of the four markets. Our overall empirical results show that (i) Tobin's Q has a significantly negative impact on CDS spread levels and changes in all samples except for the Korean subsample, whereas ROA plays a

[1] According to Benos, Wetherilt and Zikes (2013), the UK CDS market is relatively small in terms of values traded and trading frequency.

significantly negative role in explaining the level of CDS spreads mainly in the full sample and in some subsamples; (ii) stock market returns and the risk-free interest rate have a significantly negative impact on CDS spread levels and changes in all samples except for the Korean subsample, whereas the GDP growth rate is significant with the expected sign in only the Korean and French subsamples; (iii) followed by the interest rate and stock market returns, Tobin's Q has the strongest economic significance; (iv) GDP volatility and stock market volatility have a significant positive impact on CDS spread levels and changes only in Asian economies; and (v) a significantly positive relationship exists between the 2007 global financial crisis and CDS spread levels, primarily for the full sample.

The rest of this paper is structured as follows. Section 2 reviews scholarly advances in the study of CDS spreads. Section 3 describes our analytical framework in terms of hypothesis setting. In Section 4, we provide a brief discussion of our estimation methodology; variables; models, and data used. Section 5 provides an analysis of the empirical results. In Section 6, we conduct two robustness checks on our estimation results: (i) we expand our regressions by introducing a firm performance dummy variable as an explanatory variable; and (ii) we discuss the values of the adjusted R^2 and F-statistics of the redundant fixed-effects test. Section 7 concludes.

2. Literature Review

The literature on CDS spreads can be divided into two main strands. Studies in the first strand focus on reduced-form models and examine the random shocks that affect CDS pricing; such studies often employ an event study methodology. Studies in the second strand apply structural models under the assumption that CDS spreads are driven by the default risk of the CDS reference entity. Thus, researchers in this strand of literature believe that CDS spreads function as an indicator of default risk that is triggered when the reference firm's value falls below some threshold; in other words, the level of default risk is priced accordingly in CDS spreads. Although a vast body of studies have examined the determinants of credit spreads by utilizing both models, Collin-Dufresne, Goldstein, and Martin (2001) and Duffie and Singleton (1997) offer succinct summaries of the empirical findings to date. They maintain that the explanatory power of many theoretical models is rather limited and that further search for additional deterministic factors is desirable.

2.1. Reduced-Form Models

The development of reduced-form models began relatively recently in the 1990s. Some key researchers who have contributed to the development of such models include Lando (1994, 1998); Madan and Unal (1998); Jarrow and Turnbull (1995); Jarrow, Lando and Turnbull (1997); Duffie and Singleton (1999); Hull and White (2000, 2001); Duffie and Lando (2001); Zhang *et al*. (2009); Doshi *et al*. (2013); Augustin and Tédongap (2016); and Galil *et al*. (2014). The underlying assumption of reduced-form models is rather different from that of structural models, in that the former treat default as an exogenously determined random shock, and as such, firm-specific factors or indeed any variables that could affect firm performance contain no information on the firm's default probability. Despite the development of reduced-form models, many researchers prefer to use structural models because they perceive the lack of an economic rationale for reduced-form models as a major obstacle to applying such models and explaining their results.

2.2. Structural Models

Structural models are based on the option pricing model originally developed by Black and Scholes (1973) and Merton (1974). Unlike reduced-form models, structural models provide an intuitive framework for the deterministic relationship between credit risk factors and CDS spreads. Recent studies based on structural models, including Longstaff, Mithal and Neis (2005), Blanco, Brennan and Marsh (2005) and Tang and Yan (2006). These researches demonstrate that credit spreads have a negative relationship with interest rates and that while they vary with economic conditions, firm characteristics have significant explanatory power for credit spreads. Aunon-Nerin, Cossin, Hricko, and Huang (2002) study CDS determinants by examining both macroeconomic and firm-specific variables such as asset volatility, stock price, leverage, rating, and market capitalization, and they conclude that these variables explain up to 82% of CDS pricing. Equivalently, Abid and Naifar (2006) examine the explanatory power of a structural model by estimating variables such as ratings, CDS contract maturity, stock volatility, risk-free interest rates and the slopes of yield curves and report that these variables can help to explain more than 60% of CDS pricing. Other contributions to the study of CDS determinants using the structure model framework include: Acharya and Pedersen (2005), Tang and Yan (2007), and Chen, Lesmond, and Wei (2007). Specifically, Collin-Dufresne *et al*. (2001) investigate the determinants of CDS spread changes by using monthly US industrial bond data and find explanatory power for both firm leverage and implied volatility. Although with limited statistical evidence (25% explanatory power of observed credit spread changes), their paper highlights the elusive nature of some of the more fundamental problems in the search for factors that help to explain credit spreads.

3. The Hypotheses

Our study of CDS spread determinants is also based on the structural model approach, as we analyze both firm-specific and macroeconomic factors. To facilitate our investigations, we develop four testable hypotheses. Hypothesis One (H1) entails the testing of firm-specific factors in the CDS determination. Previous studies such as Ericsson *et al*. (2009) and Galil *et al*. (2014) include one firm performance related variable – leverage, in their work, our paper extends the investigation by introducing three firm performance variables. This approach adds further vigorousness to the CDS research, and it forms a major contribution of this paper to the understanding of CDS determinants. Hypothesis Two (H2) follows closely the spirit of those work such as Tang and Yan (2006); Duffie, Saita and Wang (2007); and Baum and Wan (2010), in which the influence of macroeconomic conditions is maintained and tested. Hypothesis Three (H3) shares the consideration of Stulz (2010) and Chiaramonte and Casu (2013), by speculating an impact of financial crisis on the CDS markets. Similar to Doshi *et al*. (2014), Hypothesis Four (H4) assesses whether regional factor plays a role in CDS determination. The four hypotheses are summarized as follows:

H1: Microeconomic factors such as firm performance contain information about CDS and ΔCDS.

H2: Macroeconomic conditions, as captured by GDP, stock market returns and the interest rate, have explanatory power for CDS and ΔCDS.

H3: The global financial crisis of 2007Q3-2009Q2 affected CDS and ΔCDS.

H4: A geographic effect plays a role in the determination of CDS and ΔCDS.

4. Methodology and Data

4.1. Method

As our dataset contains both cross-sectional and time-series dimensions, an unbalanced panel data estimation approach is adopted. Fixed effects with White Cross-Section Robust Standard Errors[2] that

[2] These standard errors are robust to heteroscedasticity and contemporaneous correlation among cross sections.

control for heteroscedasticity and autocorrelation are applied.[3] Since our sample contains data with a time dimension, we estimate our regressions with an AR(1) process to account for the non-instantaneous adjustment of CDS spreads to changes in the explanatory variables.[4] As a unique feature of this paper, in addition to estimating regressions for the full sample (4-Market) and hence treating all four markets as a single, homogenous market within the full sample dataset, we also estimate regressions for the reference entities in the four markets individually. Treating the data from all four markets as a single dataset implicitly assumes that these four national CDS markets are identical. This assumption is then relaxed in the second part of the regression process. We believe that this estimation method provides us with an opportunity to identify the possible existence of market-specific factors—which we term “geographic effect”[5]—that are obscured in the aggregated data, which adds robustness to our overall empirical results.

4.2. Variables

In contrast to Collin-Dufresne *et al*. (2001) and Galil *et al*. (2014), who investigate only CDS spread changes, in the eight equations that we test in this paper, we use two dependent variables, namely, CDS spread levels and changes, and 17 explanatory variables (level and change): three firm performance measures (ROA, ROE, and Tobin’s Q); two economic indicators (GDP growth and GDP volatility); two stock market indicators (stock market returns and volatility); one interest rate (the 5-year swap rate); a financial crisis dummy; and an AR(1) error term. In this paper, all changes in explanatory variables are measured by using the formula $\Delta X_i = X_t - X_{t-1}$.

4.2.1. CDS Spreads

In this paper, we use “*CDS*” and “*ΔCDS*” ($\Delta CDS_t = CDS_t - CDS_{t-1}$) to represent CDS spread levels and CDS spread changes, respectively, which are the two independent variables in our regressions.

4.2.2. Firm Performance

As a major extension to Ericsson *et al*. (2009) and Galil *et al*. (2014),[6] three firm performance ratios are used in our study. The first ratio is return on assets (*ROA*), which is calculated by dividing a firm’s net income (*NI*) by its total assets (*TA*).[7] *ROA* measures firm profitability. As profitability increases, the probability of default decreases, and *CDS* declines. Alternatively, firm performance can be measured by

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[3] A key assumption of the least squares regression is that no omitted variables are correlated with the explanatory variables; otherwise, the estimates would be biased. The advantage of using fixed effects is that by assuming a constant α_i, where $\alpha_i = \alpha + \lambda z_i$ as a unique constant for each firm, we can include the unobservable variable z in the equation $y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$, thus rendering the least squares method possible. In this setup, the slope coefficient β is the same for all *i* cross-sectional entities; however, the intercept terms α_i vary across i but are constant over time. As we incorporate firm-specific effects on the CDS spread relationship, a model allowing for a different intercept for each individual reference entity would be the preferred estimation technique. Furthermore, our sample includes CDS spreads and firm-specific accounting data; hence, they would unlikely satisfy the standard assumption for estimating random effects on a random sample.

[4] We also estimate regressions on our two models without the AR(1) error structure and find that estimation results do not differ substantially. The results are available upon request.

[5] If transaction costs (inventory costs, order handling costs, and search costs) can be assumed to be constant across markets, differences should not exist between our aggregate-level and market-level regression results.

[6] Only firm leverage is included in their regressions.

[7] $ROA = \frac{NI}{TA}$.

return on equity (*ROE*), which is equal to net income divided by total equity (*TE*).[8] As *ROE* represents the return to shareholders on their equity, a higher ratio indicates a lower likelihood of default and therefore a lower *CDS*. Another commonly used indicator of firm performance is Tobin's Q (*TBQ*), which is defined as the ratio of the market value of the firm to the replacement cost of its assets.[9] When Tobin's Q is greater than one, the current value of a firm's assets is higher than the replacement cost, i.e., the firm is performing well, and the probability of default and *CDS* decline. The same logic can be applied to relationship between CDS spread changes and changes in these firm performance indicators. For example, when ΔROA is positive, the firm is performing well, and ΔCDS will be negative; hence, we continue to expect a negative relationship. Since the calculations of the three firm performance ratios share data such as net income, total income and total equity, a high degree of correlation may exist among them. Table 1 reports the correlations among these ratios, and the correlations between ROA and ROE range from 55% to 81%. To avoid potential multicollinearity problems, we estimate the three firm performance indicators separately in Model 1 and Model 2.

Table 1. ROA, ROE, and Tobin's Q correlations

	ROA	*ROE*
	4-Market	
ROE	0.55	
TBQ	0.42	0.16
	KOR	
ROE	0.70	
TBQ	0.66	0.67
	HKG	
ROE	0.81	
TBQ	0.12	0.33
	FRA	
ROE	0.55	
TBQ	0.50	0.13
	GER	
ROE	0.74	
TBQ	0.54	0.29

4.2.3. Macroeconomic Conditions

A number of authors recognize the importance of macroeconomic conditions in the determination of credit spreads. For instance, Fama and French (1989), Korajczyk and Levy (2003) and Duffie *et al*. (2007) all document the contribution of macroeconomic conditions to credit spreads. In this paper, we examine the effects of a country's macroeconomic conditions from three perspectives: economy, financial, and interest

[8] $ROE = \frac{NI}{TE}$.

[9] $Tobin's\ Q = \frac{MVE + DEBT}{TA}$, where MVE is the market value of equity and DEBT represents the firm's book value of debts (liabilities). MVE is the product of the bank's closing share price at the end of the financial year and the number of common stock shares outstanding, DEBT is the book value of the bank's short-term debt plus the book value of the bank's long-term debt and TA is the book value of the total assets of the bank. As stated above, all of these required inputs are readily obtainable from the bank's basic financial and accounting information.

rates.[10] Fluctuations in GDP are important indicators of the macroeconomic condition of an economy (e.g.,Tang and Yan, 2006). We study the economic health of a country by using two GDP variables - GDP growth rate (*YGRT*)[11] and GDP volatility (*YVOL*), which is the conditional volatility obtained from estimating a GARCH (1, 1) model.[12] Our volatility measure is similar to that of Byrne and Davies (2005), Driver, Temple and Urga (2005), and Baum and Wan (2010). We expect a negative relationship between GDP growth and CDS spreads because when the economy is growing, business confidence increases, firm profitability rises, and hence CDS spreads decrease. By contrast, we expect the opposite relationship for GDP volatility, i.e., when fluctuations increase, economic uncertainty rises, the probability of firm default increases, and hence changes in CDS spreads increase.

The findings of Collin-Dufresne *et al*. (2001), Acharya and Johnson (2007) and Arnold and Vrugt (2008) show that stock market returns and volatility are important indicators of changes in the business climate. According to the contingent-claims framework, the features of a CDS resemble those of a short put option. As volatility increases option values, the link between CDS spreads and volatility becomes apparent. A positive stock return signifies a healthy business climate, and default risk is hence lower, or the probability of recovery is higher. By contrast, a more volatile stock market increases the likelihood of firm default. Overall, we believe that the functioning and movements of the stock market are important factors that we want to test in the CDS relationship. Unlike Collin-Dufresne *et al*. (2001) and Galil *et al*. (2014), who use a stock market volatility index, we calculate stock market returns (*SRTN*)[13] by using the stock index closing price (*P*) of the relevant country, and analogous to the GDP volatility computation, the stock market volatility (*SVOL*) calculation relies on the estimation of a GARCH (1,1) model. We expect that as stock market returns increase, economic confidence rises, and *CDS* decreases. Hence, a negative relationship should exist between stock market volatility and *CDS*. Moreover, we expect a positive relationship between CDS spreads and stock market volatility because when the business climate becomes more unstable, stock market volatility increases and *CDS* increases accordingly. As for the changes in the economic environment, we expect the same relationship for *ΔCDS*: when the change in economic volatility is positive, i.e., stability decreases, *ΔCDS* increases.

Many previous studies include risk-free interest rates in their analyses. For instance, both Longstaff and Schwartz (1995) and Blanco *et al*. (2005) show that the risk-free rate contains information about CDS spreads. To study its effects, we use the 5-year swap rate (*SWP*)[14] as a proxy for the risk-free interest rate, which determines the risk-adjusted drift of firm value. Therefore, an increase in the risk-free rate would tend to decrease risk-adjusted default probabilities and hence CDS spreads. We thus expect a negative relationship between the risk-free rate and CDS spreads. A positive change, i.e., rise, in the risk-free rate signals a decline in default probability, and hence, CDS spreads will fall. However, for a negative change, i.e., fall, in the risk-free rate, a negative *ΔCDS* follows, and *vice versa*; therefore, a negative relationship between the risk-free rate and *ΔCDS* is expected.

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[10] Our approach differs from that of Collin-Dufresne *et al*. (2001) in this respect, as they use only stock market (S&P 500) returns as a proxy for overall economic conditions.

[11] $YGRT_t = \ln\left(\frac{GDP_t}{GDP_{t-1}}\right)$.

[12] A GARCH (1, 1) model specifies that the conditional variance is a function of an intercept, a shock from the prior period and the variance from the last period. A similar approach employing a conditional volatility measure with more detailed descriptions can be found in Li (2007).

[13] $SRTN_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$.

[14] These rates are 5-year government CDS spreads, sometimes also called the LIBOR zero rates, and they are considered to correspond closely to the opportunity cost of capital. See Blanco *et al*. (2005) for discussions on swap rates as risk-free rates.

4.2.4. Crisis

The impact of the global financial crisis that began in 2007 has become an important consideration in recent research on the determinants of CDS spreads (see, e.g., Chiaramonte & Casu, 2013; Kress, 2011; Stulz, 2010; and Dickinson, 2008). To capture the potential effects of this global financial crisis on our hypothesized CDS spread relationships, the dummy variable *Crisis* is included in our estimations. This dummy variable is constructed by assigning "1" to the period from 2007Q3 through 2009Q2 and "0" for the rest of the sample. Many studies[15] on the crisis effect divide their full sample into pre-crisis and post-crisis periods and examine the differences between them. Owing to the relatively limited size of our sample, we believe that directly containing a crisis variable in our regression equations would be the preferred approach to minimize the small sample bias problem. For the purposes of our hypothesis testing, a positive relationship is expected between the crisis variable and our *CDS* and *ΔCDS* dependent variables. Table 2 displays the expected signs of the explanatory variables discussed above.

Table 2. Explanatory variable and expected signs on estimated coefficients

Explanatory variable	Description	Dependent variable *CDS*
ROA	Return on assets	-
ROE	Return on equity	-
TBQ	Tobin's Q	-
PDMY	Firm performance dummy	-
YGRT	GDP growth rate	-
YVOL	GDP volatility	+
SRTN	Stock market return	-
SVOL	Stock market volatility	+
SWP	Swap rate	-
Crisis	Crisis period dummy	+
		ΔCDS
Δ*ROA*	Change in return on assets	-
Δ*ROE*	Change in return on equity	-
Δ*TBQ*	Change in Tobin's Q	-
Δ*PDMY*	Change in firm performance dummy	-
Δ*YGRT*	Change in GDP growth rate	-
Δ*YVOL*	Change in GDP volatility	+
Δ*SRTN*	Change in stock market return	-
Δ*SVOL*	Change in stock market volatility	+
Δ*SWP*	Change in swap rate	-
Crisis	Crisis period dummy	+

4.3. Models

Generally, the four hypotheses underlying our study can be represented by the following equation:

$$Credit\ Default\ Swap_{i,t} = \alpha + \beta_1 Micro_{i,t} + \beta_2 Macro_{i,t} + \beta_3 Crisis_{i,t} + \varepsilon_{i,t} \qquad \text{(M)}$$

[15] E.g. Galil *et al*. (2014).

where the dependent variable, $Credt\ Default\ Swap_{i,t}$ represents the CDS spread (level and change) of the reference entity *i* at time *t*; $Micro$ represents the microeconomic conditions or, more precisely, a vector of firm-specific variables indicative of the financial performance of firm *i* at time *t*; $Macro$ is a vector of variables (GDP, stock market, swap rate) that captures the macroeconomic conditions of the relevant market; and $Crisis$ serves as a dummy variable that takes the value "1" for the period 2007Q3-2009Q2 and zero otherwise.

To perform our hypothesis testing, two models are derived from equation (M). The formation of Model 1 is similar to that in Tang and Yan (2007), Acharya and Johnson (2007) and Pires, Pereira and Martins (2010) in which CDS spread levels are investigated as the dependent variable and the levels of explanatory variables are examined. Model 2 is considered a dynamic version of Model 1 in which *ΔCDS* is used as the dependent variable and changes in both firm performance indicators and macroeconomic measures are studied.

Model 1:

$$CDS_{i,t}^{n} = \alpha + \beta_1 ROA_{i,t}^{n} + \beta_2 YGRT_t^{n} + \beta_3 YVOL_t^{n} + \beta_4 SRTN_t^{n} + \beta_5 SVOL_t^{n} + \beta_6 SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (1a)$$

$$CDS_{i,t}^{n} = \alpha + \beta_1 ROE_{i,t}^{n} + \beta_2 YGRT_t^{n} + \beta_3 YVOL_t^{n} + \beta_4 SRTN_t^{n} + \beta_5 SVOL_t^{n} + \beta_6 SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (1b)$$

$$CDS_{i,t}^{n} = \alpha + \beta_1 TBQ_{i,t}^{n} + \beta_2 YGRT_t^{n} + \beta_3 YVOL_t^{n} + \beta_4 SRTN_t^{n} + \beta_5 SVOL_t^{n} + \beta_6 SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (1c)$$

Model 2:

$$\Delta CDS_{i,t}^{n} = \alpha + \beta_1 \Delta ROA_{i,t}^{n} + \beta_2 \Delta YGRT_t^{n} + \beta_3 \Delta YVOL_t^{n} + \beta_4 \Delta SRTN_t^{n} + \beta_5 \Delta SVOL_t^{n} + \beta_6 \Delta SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (2a)$$

$$\Delta CDS_{i,t}^{n} = \alpha + \beta_1 \Delta ROE_{i,t}^{n} + \beta_2 \Delta YGRT_t^{n} + \beta_3 \Delta YVOL_t^{n} + \beta_4 \Delta SRTN_t^{n} + \beta_5 \Delta SVOL_t^{n} + \beta_6 \Delta SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (2b)$$

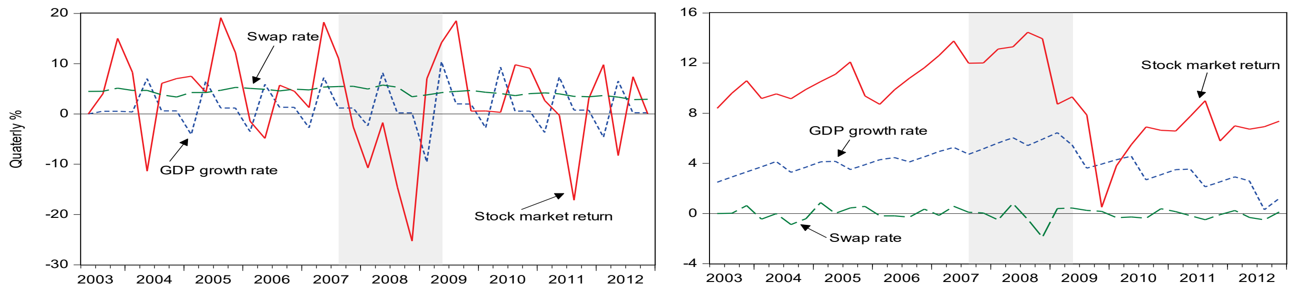
$$\Delta CDS_{i,t}^{n} = \alpha + \beta_1 \Delta TBQ_{i,t}^{n} + \beta_2 \Delta YGRT_t^{n} + \beta_3 \Delta YVOL_t^{n} + \beta_4 \Delta SRTN_t^{n} + \beta_5 \Delta SVOL_t^{n} + \beta_6 \Delta SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (2c)$$

where, n = 1,..,4 (number of markets). i is the number of reference entities: $i = 9$ for KOR; $i = 8$ for HKG; $i = 54$ for FRA; and $i = 41$ for GER. The sample periods are as follows: 4-Market, 2001Q2 to 2012Q4; KOR, 2003Q2 to 2012Q4; HKG, 2003Q3 to 2012Q4; FRA, 2001Q2 to 2012Q4; and GER, 2001Q3 to 2012Q4. α is the intercept term, $\beta_1, \ldots, \beta_7$ are the slope coefficients, and $\varepsilon^{n}_{i,t}$ is an idiosyncratic error term.

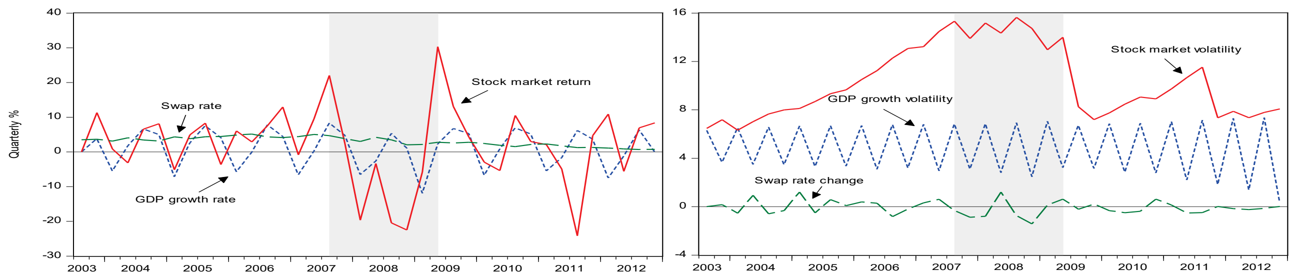
4.4. Data

All the data for our estimations are collected from Bloomberg, and calculations are performed wherever necessary to compute the required variables. Although daily CDS and stock market index prices are available, our samples are constrained by the availability of GDP and firm-level balance sheet and income statement data, which are listed only annually (South Korea); semiannually (Hong Kong and France); and quarterly (Germany). In the first three cases, following Collin-Dufresne *et al*. (2001), Tang and Yan (2007), and Ericsson *et al*. (2009), we apply linear interpolation to obtain quarterly data for the first three markets. To ensure the dynamic nature of our dataset, we omit firms with inactive CDS spread changes for four or more consecutive quarters. In total, we have 112 single-name reference entities with 3931 quarterly observations. The names of the reference entities and their credit ratings according to the three main ratings agencies are presented in the Appendix.

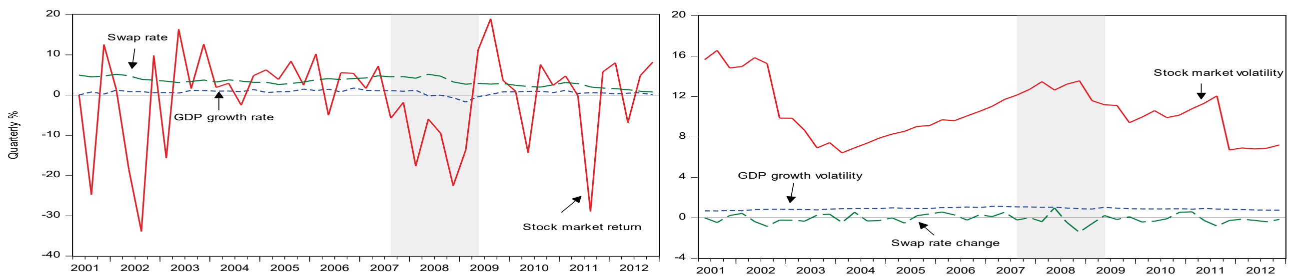
Panel A: KOR



Panel B: HKG



Panel C: FRA



Panel D: GER

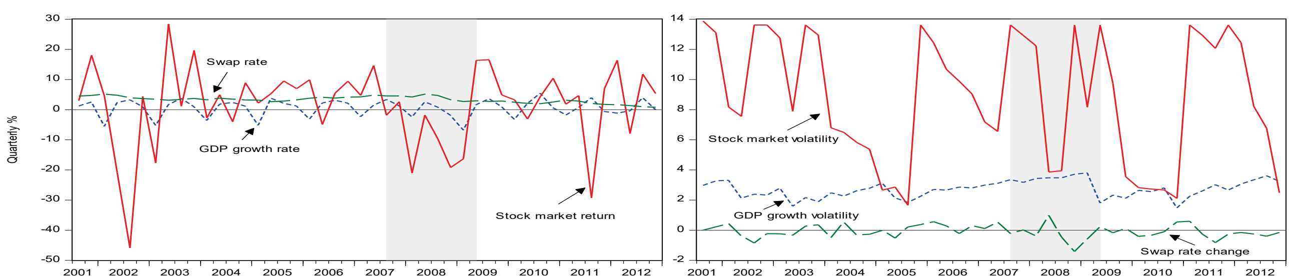


Figure 1. Individual market – GDP growth, stock market return and swap rate movements (level and volatility)

Figure 1 graphically displays the relationships among our explanatory variables in the four markets over time. From the left sides of the four panels, we observe that stock market returns fluctuate more than GDP growth and swap rates. These changes are supported by a high degree of stock market volatility in the right-hand panels for each market, particularly for HKG and GER. Excess movements in the KOR and HKG stock markets during 2007-2008 are also clearly visible. This figure reveals that the global financial crisis affected these variables.

5. Empirical Results

5.1. 4-Market

Table 3. Estimation results for 4-Market

Sample period: 2001Q2 to 2012Q4				No. of reference entity = 112, N = 3931			
	Model 1				Model 2		
Explanatory variable	Dependent variable: *CDS*			Explanatory variable	Dependent variable: Δ*CDS*		
	Eq.1a	Eq.1b	Eq.1c		Eq.2a	Eq.2b	Eq.2c
ROA	**-6.008****			*ROA*	-3.572		
	(-2.041)				(-1.308)		
ROE		-0.914		*ROE*		-0.504	
		(-1.407)				(-0.947)	
TBQ			**-129.203*****	*TBQ*			**-136.356*****
			(-3.130)				(-3.811)
YGRT	**-1.833***	**-1.829***	**-1.823***	*YGRT*	-1.611	-1.611	-1.635
	(-1.672)	(-1.682)	(-1.719)		(-1.224)	(-1.227)	(-1.280)
YVOL	-0.268	-0.309	-0.416	*YVOL*	-0.785	-0.790	-0.883
	(-0.134)	(-0.148)	(-0.204)		(-0.332)	(-0.325)	(-0.373)
SRTN	**-1.638*****	**-1.626*****	**-1.533*****	*SRTN*	**-1.689*****	**-1.682*****	**-1.578*****
	(-3.804)	(-3.809)	(-3.918)		(-4.475)	(-4.475)	(-4.516)
SVOL	0.489	0.464	0.538	*SVOL*	0.416	0.400	0.505
	(0.449)	(0.427)	(0.527)		(0.348)	(0.332)	(0.430)
SWP	**-43.771*****	**-44.212*****	**-41.260*****	*SWP*	**-46.354*****	**-46.724*****	**-44.843*****
	(-3.048)	(-3.022)	(-2.933)		(-2.735)	(-2.727)	(-2.597)
Crisis	**59.645***	**59.418***	**54.328***	*Crisis*	17.780	18.544	15.405
	(1.807)	(1.793)	(1.743)		(1.031)	(1.066)	(0.886)
AR(1)	**0.696*****	**0.702*****	**0.704*****	*AR(1)*	-0.005	-0.004	-0.010
	(9.286)	(9.452)	(9.747)		(-0.036)	(-0.026)	(-0.076)
Adjusted R^2	0.740	0.739	0.741		0.108	0.106	0.115

Notes: Associated *t*-ratios in parentheses. Significant statistics are in bold.
***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.
Intercept estimates are not shown.

Table 3 presents the estimation results from the 4-Market aggregated sample. The results from both Models 1 and 2 statistically demonstrate that both *TBQ* and *ΔTBQ* have explanatory power for *CDS* and *ΔCDS*, respectively, with the expected signs. Moreover, in all six equations, the highly statistically significant coefficients for *STRN* and *ΔSTRN* signify that both *CDS* and *ΔCDS* decline when stock market returns increase and when positive changes in stock market returns occur. Our results are in agreement with Galil *et al*. (2014), who report a negative and significant relationship. As explained above, we are not surprised by the existence of these negative slope coefficients, as they indicate that CDS spread levels and changes decrease whenever business performance or the macroeconomic environment improves. Further explanatory variables that produce consistently significant estimation results are *SWP* and *ΔSWP*. Again, we obtain the expected signs. The negative coefficients for these variables suggest that a rise in the interest rate leads to a decrease in CDS spread levels and changes, clearly supporting our theoretical understanding of their relationship.

Furthermore, the magnitude and negative sign of all six variables mentioned above demonstrate that the economic significance of the firm performance measures (*TBQ* and *ΔTBQ*) is rather strong: the factor loading on these two variables is three times larger than the factor loading on the risk-free interest rate (*SWP* and *ΔSWP*) and over 80 times larger than the factor loading on the business climate indicators (*STRN* and *ΔSTRN*). It is also very interesting that all of the above variables are market value indicators rather than book value indicators, implying that risk managers and policy makers should pay more attention to market data in forecasting the default risk of the reference entities. The following differences in results between Models 1 and 2 are notable: 1) *ROA* contains information on *CDS* in the expected manner; 2) the recent global financial crisis of 2007-2009 had marginal effects on *CDS*; and 3) adjustments in *CDS* in response to the explanatory variables are rather slow; hence, significant AR(1) coefficients persist in Model 1.

5.2. KOR and HKG

Table 4. Estimation results for KOR

Sample period: 2003Q2 to 2012Q4				No. of reference entity = 9, N = 293			
	Model 1				Model 2		
Explanatory variable	Dependent variable: *CDS*			Explanatory variable	Dependent variable: Δ*CDS*		
	Eq.1a	Eq.1b	Eq.1c		Eq.2a	Eq.2b	Eq.2c
ROA	**-5.208****			*ROA*	-1.040		
	(-2.430)				(-0.583)		
ROE		-1.807		*ROE*		1.744	
		(-1.539)				(1.701)	
TBQ			-14.429	*TBQ*			48.437
			(-0.470)				(1.407)
YGRT	**-3.191****	**-3.216****	**-3.175****	*YGT*	**-3.634****	**-3.617****	**-3.591****
	(-2.502)	(-2.530)	(-2.496)		(-2.189)	(-2.200)	(-2.191)
YVOL	**26.624***	**26.506***	**25.825***	*YVOL*	**31.766****	**31.275****	**31.515****
	(1.725)	(1.677)	(1.673)		(2.265)	(2.247)	(2.263)
SRTN	-1.116	1.097	-1.071	*SRTN*	**-1.222***	**-1.191***	**-1.210***
	(-1.206)	(-1.177)	(-1.143)		(-1.794)	(-1.768)	(-1.763)
SVOL	2.804	2.732	2.309	*SVOL*	**6.591****	**6.271****	**6.408****
	(0.760)	(0.743)	(0.614)		(2.392)	(2.323)	(2.323)
SWP	**-55.220*****	**-54.400*****	**-54.772*****	*SWP*	**-46.574*****	**-46.644*****	**-46.6c29*****
	(-3.889)	(-3.762)	(-3.703)		(-5.123)	(-5.239)	(-5.164)
Crisis	33.596	35.131	33.860	*Crisis*	21.428	23.052	21.790
	(1.017)	(1.063)	(1.059)		(1.378)	(1.528)	(1.427)
AR(1)	**0.687*****	**0.690*****	**0.709*****	*AR(1)*	-0.169	-0.175	-0.170
	(5.188)	(5.156)	(5.153)		(-1.115)	(-1.167)	(-1.128)
Adjusted R^2	0.773	0.771	0.770		0.426	0.428	0.428

Notes: Associated *t*-ratios in parentheses. Significant statistics are in bold.

***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.

Intercept estimates are not shown.

Table 4 presents the results for KOR. The results of both models show that *SWP* (*ΔSWP*), *YGRT* (*ΔYGRT*) and *YVOL* (*ΔYVOL*) contain information on *CDS* (*ΔCDS*). Moreover, *ΔSRTN* and *ΔSVOL* are found to affect *ΔCDS*, whereas *ROA* is found to possess explanatory power for *CDS*. All statistically significant coefficients take the expected signs in both the *CDS* and the *ΔCDS* spread specifications. Listed in Table 5, the estimation results for HKG rather differ from those for KOR. Specifically, the reported results show that *TBQ* (*ΔTBQ*), *SRTN* (*ΔSRTN*), *SVOL* (*ΔSVOL*), and *SWP* (*ΔSWP*) are important determinants of *CDS* (*ΔCDS*). Again, we obtain the expected signs for all the statistically significant coefficients, and *ROA* continues to be the variable with explanatory power for *CDS*.

Table 5. Estimation results for HKG

Sample period: 2003Q3 to 2012Q4				No. of reference entity = 8, *N* = 221			
	Model 1				Model 2		
Explanatory variable	Dependent variable: *CDS*			Explanatory variable	Dependent variable: Δ*CDS*		
	Eq.1a	Eq.1b	Eq.1c		Eq.2a	Eq.2b	Eq.2c
ROA	**-3.362****			*ROA*	-2.469		
	(-2.139)				(-0.866)		
ROE		-0.723		*ROE*		-0.462	
		(-0.631)				(-0.266)	
TBQ			**-205.036*****	*TBQ*			**-246.519*****
			(-2.587)				(-2.775)
YGRT	-0.788	-0.839	-0.750	*YGT*	-1.103	-1.126	-1.140
	(-0.842)	(-0.868)	(-0.807)		(-1.141)	(-1.153)	(-1.248)
YVOL	-1.389	-1.421	-1.288	*YVOL*	-1.989	-2.007	-1.850
	(-0.497)	(-0.492)	(-0.480)		(-0.802)	(-0.792)	(-0.812)
SRTN	**-2.088*****	**-2.008*****	**-1.709*****	*SRTN*	**-1.919****	**-1.878****	**-1.472****
	(-3.652)	(-3.596)	(-3.435)		(-2.576)	(-2.491)	(-2.309)
SVOL	**10.347****	**10.761****	**8.937****	*SVOL*	**15.050*****	**15.487*****	**13.468*****
	(2.507)	(2.017)	(2.100)		(3.509)	(3.526)	(4.035)
SWP	**-44.214****	**-46.495*****	**-39.381*****	*SWP*	**-52.519*****	**-53.462*****	**-52.325*****
	(-3.102)	(-2.908)	(-2.863)		(-2.923)	(-2.867)	(-2.988)
Crisis	45.870	46.178	**48.874***	*Crisis*	20.669	22.722	18.881
	(1.522)	(1.448)	(1.818)		(1.162)	(1.247)	(1.297)
AR(1)	**0.605*****	**0.616*****	**0.609*****	*AR(1)*	-0.098	-0.095	-0.110
	(6.417)	(6.372)	(6.767)		(-0.503)	(-0.494)	(-0.615)
Adjusted R^2	0.784	0.782	0.798		0.362	0.359	0.417

Notes: Associated *t*-ratios in parentheses. Significant statistics are in bold.
***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.
Intercept estimates are not shown.

5.3. FRA and GER

Table 6 presents the results for FRA. As shown, *ROA* (*ΔROA*), *TBQ* (*ΔTBQ*), *YGRT* (*ΔYGRT*), *SRTN* (*ΔSRTN*), and *SWP* (*ΔSWP*) have significant relationships with *CDS* (*ΔCDS*). Moreover, *ΔROE* contains information on *ΔCDS*. While we obtain the expected signs for the significant coefficients except for *YVOL*, this is the first time where we find explanatory power for all firm performance indicators within the same model—Model 2. The empirical results for GER are provided in Table 7. Only *TBQ* (*ΔTBQ*), *SRTN* (*ΔSRTN*) and *SWP* (*ΔSWP*) exhibit strong deterministic relationships with *CDS* (*ΔCDS*). Again, all of the statistically significant estimated coefficients take the expected signs.

Table 6. Estimation results for FRA

Sample period: 2001Q2 to 2012Q4				No. of reference entity = 54, *N* = 1919			
	Model 1				Model 2		
Explanatory variable	Dependent variable: *CDS*			Explanatory variable	Dependent variable: *CDS*		
	Eq.1a	Eq.1b	Eq.1c		Eq.2a	Eq.2b	Eq.2c
ROA	**-6.818****			*ROA*	**-5.324****		
	(-2.128)				(-2.338)		
ROE		-1.179		*ROE*		**-1.014*****	
		(-1.641)				(-2.607)	
TBQ			**-125.754*****	*TBQ*			**-162.213*****
			(-3.280)				(-3.525)
YGRT	**-19.905***	**-20.065****	**-18.497***	*YGT*	**-18.314****	**-18.352****	**-17.305****
	(-1.948)	(-1.968)	(-1.923)		(-2.015)	(-2.018)	(-2.076)
YVOL	**-148.376****	**-144.275****	**-127.526***	*YVOL*	-83.340	-81.384	-85.934
	(-2.096)	(-2.030)	(-1.822)		(-0.822)	(-0.807)	(-0.908)
SRTN	**-1.873*****	**-1.883*****	**-1.867*****	*SRTN*	**-2.341*****	**-2.336*****	**-2.208*****
	(-3.903)	(-3.929)	(-4.093)		(-3.994)	(-4.020)	(-3.995)
SVOL	3.902	3.855	3.654	*SVOL*	-0.761	-0.629	0.156
	(0.436)	(0.430)	(0.420)		(-0.087)	(-0.072)	(0.019)
SWP	**-33.147*****	**-33.446*****	**-31.036*****	*SWP*	**-34.724****	**-35.497****	**-33.788****
	(-2.912)	(-2.877)	(-2.709)		(-2.373)	(-2.390)	(-2.280)
Crisis	40.088	38.633	32.410	*Crisis*	13.598	13.889	10.363
	(1.345)	(1.296)	(1.154)		(1.069)	(1.076)	(0.804)
AR(1)	**0.718*****	**0.724*****	**0.741*****	*AR(1)*	-0.089	-0.088	-0.089
	(10.791)	(11.172)	(11.976)		(-0.791)	(0.431)	(-0.815)
Adjusted R^2	0.797	0.795	0.797		0.170	0.169	0.178

Notes: Associated *t*-ratios in parentheses. Significant statistics are in bold.

***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.

Intercept estimates are not shown.

Table 7. Estimation results for GER

Sample period: 2001Q3 to 2012Q4				No. of reference entity = 41, *N* = 1498			
	Model 1				Model 2		
Explanatory variable	Dependent variable: *CDS*			Explanatory variable	Dependent variable: *CDS*		
	Eq.1a	Eq.1b	Eq.1c		Eq.2a	Eq.2b	Eq.2c
ROA	-5.504			*ROA*	-0.968		
	(-1.278)				(-0.208)		
ROE		-0.610		*ROE*		0.180	
		(-0.737)				(0.205)	
TBQ			**-173.145****	*TBQ*			**-113.942****
			(-2.202)				(-2.556)
YGRT	-1.606	-1.611	-1.652	*YGT*	-1.377	-1.389	-1.413
	(-0.995)	(-1.006)	(-1.060)		(-0.934)	(-0.939)	(-0.982)
YVOL	7.181	7.073	7.102	*YVOL*	3.812	3.976	3.448
	(0.650)	(0.654)	(0.660)		(0.301)	(0.316)	(0.280)
SRTN	**-1.190*****	**-1.181*****	**-1.000*****	*SRTN*	**-1.207*****	**-1.196*****	**-1.094*****
	(-3.074)	(-3.085)	(-2.937)		(-3.854)	(-3.841)	(-3.814)
SVOL	-0.433	-0.454	-0.452	*SVOL*	-0.234	-0.249	-0.214
	(-0.386)	(-0.399)	(-0.415)		(-0.230)	(-0.238)	(-0.208)
SWP	**-45.473*****	**-45.846*****	**-42.251*****	*SWP*	**-49.560****	**-50.056****	**-47.255****
	(-2.861)	(-2.858)	(-2.895)		(-2.309)	(-2.328)	(-2.167)
Crisis	**73.711***	**73.119***	**67.759***	*Crisis*	22.174	23.266	18.682
	(1.719)	(1.716)	(1.725)		(1.112)	(1.157)	(0.904)
AR(1)	**0.675*****	**0.681*****	**0.665*****	*AR(1)*	0.037	0.037	0.032
	(6.875)	(7.005)	(6.828)		(0.224)	(0.226)	(0.194)
Adjusted R^2	0.683	0.682	0.686		0.056	0.056	0.061

Notes: Associated *t*-ratios in parentheses. Significant statistics are in bold.
***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.
Intercept estimates are not shown.

5.4. Hypothesis Testing Synopsis

Synthesizing our overall results, we gather the following statement regarding our four hypotheses:

(i) *TBQ* (*ΔTBQ*) has a significantly negative impact on *CDS* (*ΔCDS*) in all samples except for Korea, whereas *ROA* plays a significantly negative role in explaining *CDS* mainly in the full sample and in some individual subsamples. This result lends general support to H1.

(ii) *SRTN* (*ΔSRTN*) and *SWP* (*ΔSWP*) have a significantly negative impact on *CDS* (*ΔCDS*) in all samples except for Korea, whereas *YGDP* (*ΔYGDP*) is significant with the expected sign only for Korea and France. Thus, H2 cannot be rejected. Moreover, followed by *SWP* (*ΔSWP*) and *STRN* (*ΔSTRN*) in most cases, *TBQ* (*ΔTBQ*) has the greatest magnitude in terms of economic significance and a negative sign, which reemphasizes the importance of the market value indicators in developing risk management strategy.

(iii) A significantly positive relationship is observed between *Crisis* and *CDS* mainly in the full sample, which suggests that H3 is weakly supported.

(iv) *YVOL* (*ΔYVOL*), and in particular *SVOL* (*ΔSVOL*) are found to have a significant positive impact on *CDS* (*ΔCDS*) only in Asian economies, implying that the two Asian markets are more sensitive to market volatility. In other words, market players might have more confidence in the two European economies, which marginally supports H4.

6. Robustness

6.1. Firm Performance Dummy

To account for all of the firm performance information embedded in *ROA*, *ROE*, and *TBQ* and to enhance the robustness of our analysis, we construct a performance dummy (*PDMY*). This dummy variable is created by assigning the value "1" whenever either of the two accounting ratios has a change that is greater than zero, and "0" otherwise. In addition to making use of all three performance ratios, this performance dummy offers with us the opportunity to resolve the occasions in which one of the ratios is either not changing or even changing in the opposite direction of the other two ratios. Such a situation is likely to occur when variables measured in both book and market values are used.[16] Equations (3a) and (3b) below present the structure of the hypothesized relationship.

$$CDS_{i,t}^{n} = \alpha + \beta_1 PDMY_{i,t}^{n} + \beta_2 YGRT_t^{n} + \beta_3 YVOL_t^{n} + \beta_4 SRTN_t^{n} + \beta_5 SVOL_t^{n} + \beta_6 SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (3a)$$

$$\Delta CDS_{i,t}^{n} = \alpha + \beta_1 \Delta PDMY_{i,t}^{n} + \beta_2 \Delta YGRT_t^{n} + \beta_3 \Delta YVOL_t^{n} + \beta_4 \Delta SRTN_t^{n} + \beta_5 \Delta SVOL_t^{n} + \beta_6 \Delta SWP_t^{n} + \beta_7 Crisis_t + \varepsilon_{i,t}^{n} \quad (3b)$$

Both the dependent and the explanatory variables are identical to those in Equations (1a) to (2c) above, except that firm performance variables such as *ROA*, *ROE* and *TBQ* are now replaced by the two dummy variables *PDMY* and *ΔPDMY*.

The estimation results of Equations (3a) and (3b) are presented in Table 8. Generally, we can see that the results share a similar pattern with the prior results. However, one difference emerges. In the HKG, FRA and GER markets, the prior results indicate that some firm performance indicators are statistically significant variables in explaining both *CDS* and *ΔCDS*; however, these factors no longer possess explanatory power when they are instead captured by *PDMY* and *ΔPDMY*. Nevertheless, given the consistently significant appearance of the stock market and interest rate variables, overall, the results support the claim that our regression results are robust to the use of alternative explanatory variables—in the case of performance indicators—and the results from the FRA market further support our contention. Overall, we find that in many cases, the differences in the strength of our estimations used to explain CDS spread levels and changes are small and that the coefficients take the expected signs.

[16] When book values remain stable, market-valued items may fluctuate substantially.

Table 8. Estimation results for firm performance dummy variable

	Explanatory Variable								
	Panel A: 4-Markets (N = 3931)								Adjusted R^2
CDS (Eq.3a)	*PDMY*	*YGRT*	*YVOL*	*SRTN*	*SVOL*	*SWP*	*Crisis*	AR(1)	
	-8.454**	**-1.825***	-0.367	**-1.596*****	0.463	**-44.995*****	**57.812***	**0.706*****	0.738
	(-1.816)	(-1.686)	(-0.174)	(-3.875)	(0.423)	(-2.959)	(1.738)	(9.573)	
ΔCDS (Eq.3b)	*ΔPDMY*	*ΔYGRT*	*ΔYVOL*	*ΔSRTN*	*ΔSVOL*	*ΔSWP*	*Crisis*	AR(1)	
	-7.855**	-1.604	-0.791	**-1.662*****	0.387	**-47.002*****	19.370	-0.004	0.107
	(-2.044)	(-1.226)	(-0.327)	(-4.434)	(0.318)	(-2.675)	(1.079)	(-0.034)	
	Panel B: KOR (N = 293)								
CDS (Eq.3a)	*PDMY*	*YGRT*	*YVOL*	*SRTN*	*SVOL*	*SWP*	*Crisis*	AR(1)	
	-1.358	**-3.164****	**25.800***	-1.073	2.289	**-54.745*****	33.252	**0.712*****	0.770
	(-0.167)	(-2.504)	(1.675)	(-1.146)	-0.604	(-3.715)	(1.050)	(5.073)	
ΔCDS (Eq.3b)	*ΔPDMY*	*ΔYGRT*	*ΔYVOL*	*ΔSRTN*	*ΔSVOL*	*ΔSWP*	*Crisis*	AR(1)	
	-0.041	**-3.637****	**31.678****	**-1.214***	**6.534****	**-46.399*****	21.825	-0.169	0.426
	(-0.006)	(-2.192)	(2.255)	(-1.784)	(2.381)	(-5.099)	(1.420)	(-1.114)	
	Panel C: HKG (N = 221)								
CDS (Eq.3a)	*PDMY*	*YGRT*	*YVOL*	*SRTN*	*SVOL*	*SWP*	*Crisis*	AR(1)	
	-0.593	-0.865	-1.429	**-1.958*****	**10.856***	**-47.553*****	46.580	**0.619*****	0.781
	(-0.045)	(-0.898)	(-0.491)	(-3.381)	(1.873)	(-2.927)	(1.449)	(6.405)	
ΔCDS (Eq.3b)	*ΔPDMY*	*ΔYGRT*	*ΔYVOL*	*ΔSRTN*	*ΔSVOL*	*ΔSWP*	*Crisis*	AR(1)	
	-1.421	-1.136	-2.017	**-1.856****	**15.493*****	**-53.678*****	23.507	-0.094	0.359
	(-0.097)	(-1.179)	(-0.795	(-2.439)	(3.185)	(-2.829)	(1.358)	(-0.492)	
	Panel D: FRA (N = 1919)								
CDS (Eq.3a)	*PDMY*	*YGRT*	*YVOL*	*SRTN*	*SVOL*	*SWP*	*Crisis*	AR(1)	
	-18.052***	**-19.853***	**-143.664***	**-1.849*****	3.507	**-33.897*****	35.055	**0.731*****	0.795
	(-2.702)	(-1.940)	(-1.943)	(-4.020)	(0.394)	(-2.881)	(1.203)	(11.644)	
ΔCDS (Eq.3b)	*ΔPDMY*	*ΔYGRT*	*ΔYVOL*	*ΔSRTN*	*ΔSVOL*	*ΔSWP*	*Crisis*	AR(1)	
	-18.444***	**-17.618****	-82.392	**-2.283*****	-1.080	**-36.098****	15.027	-0.085	0.171
	(-3.025)	(-1.988)	(-0.839)	(-4.069)	(-0.125)	(-2.390)	(1.142)	(-0.760)	
	Panel E: GER (N = 1498)								
CDS (Eq.3a)	*PDMY*	*YGRT*	*YVOL*	*SRTN*	*SVOL*	*SWP*	*Crisis*	AR(1)	
	-0.484	-1.637	7.199	**-1.163*****	-0.448	**-46.819*****	**72.821***	**0.684*****	0.681
	(-0.103)	(-1.204)	(0.673)	(-3.086)	(-0.398)	(-2.769)	(1.699)	(7.166)	
ΔCDS (Eq.3b)	*ΔPDMY*	*ΔYGRT*	*ΔYVOL*	*ΔSRTN*	*ΔSVOL*	*ΔSWP*	*Crisis*	AR(1)	
	1.060	-1.390	3.853	**-1.203*****	-0.251	**-49.846****	22.740	0.038	0.056
	(0.271)	(-0.938)	(0.305)	(-3.973)	(-0.238)	(-2.245)	(1.058)	(0.226)	

Notes: Associated *t*-ratios in parentheses. Intercept estimates are not shown.

Significant statistics are in bold. ***, ** and * denote statistically significant levels of 1%, 5% and 10% respectively.

6.2. Analyses of the Goodness-of-Fit and Redundant Fixed-Effects Test Statistics

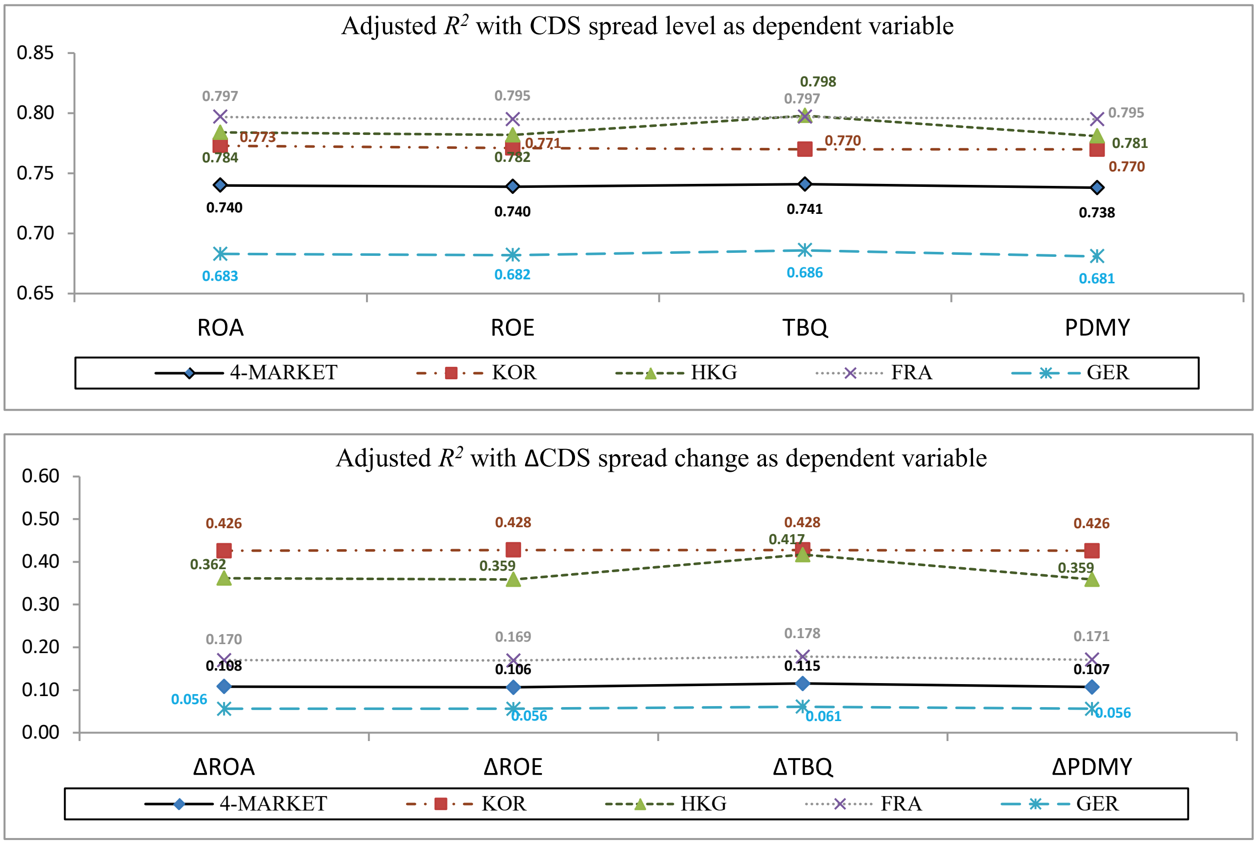


Figure 2. Goodness-of-Fit analysis

To gauge the goodness-of-fit of our regressions, we also performed an analysis of the adjusted R^2. Figure 2 displays values of the adjusted R^2 associated with all of the regressions that we have estimated. From the top half of the figure for models with *CDS* as the dependent variable, we observe that GER has the lowest goodness-of-fit results, while FRA yields the highest goodness-of-fit values. Moreover, all four performance measures produce comparable adjusted R^2 values within an approximately 10% range. The bottom half of the figure for models with *ΔCDS* as the dependent variable shows that GER again has the lowest adjusted R^2 and that KOR yields the best goodness-of-fit results. Indeed, the goodness-of-fit difference between these four performance measures and the five market categories has widened substantially to approximately 37%.[17] In other words, our results suggest that reference entities with lower credit ratings such as those in KOR and HKG exhibit greater explanatory power than those in other markets. Although this observation diverges from the results of Avramov, Jostova and Philipov (2007) and Ericsson *et al*. (2009), it is in line with those of Huang and Huang (2003) and Galil *et al*. (2014). As shown in Figure 2, regressions employing CDS spread levels as the dependent variable (Model 1) produce a set of relatively high adjusted R^2 values that range from 0.681 to 0.798, whereas those using CDS spread changes as the dependent variable (Model 2) generate relatively lower adjusted R^2 values that range from 0.056 to 0.428.[18] However, according to the redundant fixed-effects test *F*-statistics,[19] although Model 2

[17] See, for example, *ΔROE*, which has the largest difference (0.428 - 0.056) = 0.372.

[18] As further support for our claim, the models estimated by Galil *et al.* (2014) and Ericsson *et al.* (2009) using US CDS data yield only an explanatory power of 16.23% and 23%, respectively.

[19] The summary of redundant fixed effects test *F*-statistics is available upon request.

generates lower adjusted R^2 values, it seems to produce less biased results than Model 1. Therefore, to ensure the robustness of our results, we maintain that a model with a reasonably good adjusted R^2 value and relatively smaller *F*-statistics would be preferred and considered more reliable to derive our conclusion. Accordingly, estimation results using ΔCDS as the dependent variable together with changes in certain explanatory variables appears to yield findings that fulfill these criteria.

7. Conclusions

This paper attempts to study the determinants of CDS spread levels and changes by using a panel dataset covering 112 reference entities from four markets over the period 2001-2012. Employing a structural model, we establish eight equations incorporating variables that could affect the default risk of a reference entity and hence CDS spreads. Our empirical results suggest that both firm performance and macroeconomic conditions possess significant explanatory power for CDS spreads; however, market value indicators (i.e., Tobin's Q, stock market returns and the interest rate) appear to be much more important than book value indicators (i.e., ROA, ROE, and GDP growth rate) in determining CDS spread levels and changes. Followed by the interest rate and stock market returns, Tobin's Q demonstrates the strongest economic significance among the market value indicators. Therefore, both H1 and H2 cannot be rejected. H3 also cannot be rejected because the global financial crisis of 2007 significantly affect global CDS markets as a whole, but it generally did not affect the individual markets under study. The results also show that only the Asian CDS markets in the sample are sensitive to both GDP and stock market volatility, whereas the two European markets are free from such an impact. This finding lends clear support to H4, which argues for the existence of geographic effects.

On the basis of our empirical results, we can assert that any government policy that could help provide a stable stock market and generate economic growth would facilitate the functioning of CDS markets and thus enhance the use of CDSs as a risk management tool for the investment community. In particular, both risk managers and financial regulators are encouraged to devote greater attention to the market value indicators of firm performance and macroeconomic conditions. Considerable weight should be given to Tobin's Q, the risk-free interest rate and stock market returns in risk pricing. For actors dealing with CDSs in Asian markets, economic and stock market volatility should also be covered closely. Notwithstanding, while some fundamental determinants of CDSs remain elusive, further research on this subject by extending the number of markets and embracing some market-specific geopolitical variables that help produce a more precise picture of the effect of market factors on CDS pricing across countries would certainly be beneficial. This paper contributes to the research of CDS determinants in two ways. Firstly we highlight the importance of market/geographic effect, and secondly, to our best knowledge, we are the first to test for the explanatory power of our three firm performance – market and book value indicators in the formation and movements of CDS spreads.

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Appendix

Appendix 1. CDS reference entity

KOR (Total 9)				HKG (Total 8)			
Reference Entity	Moody	Fitch	S&P	Reference Entity	Moody	Fitch	S&P
Hana Bank	A3	A+	A	Hutchison Whampoa Ltd	A1	AA-	A+
Hyundai Motor Co	A3	A+	A	Hysan Development Co Ltd	A1	AA-	A+
Industrial Bank of Korea	A3	A	A-	Jardine Strategic Holdings Ltd	A1	AA-	A+
Kookmin Bank	A3	A	A-	MTR Corp Ltd	A1	AA-	A+
Korea Electric Power Corp	A3	A	A-	Noble Group Ltd	Aa2	AA-	AA
KT Corp	A3	A	A-	Sun Hung Kai Properties Ltd	Aa2	AA-	AA+
POSCO	A3	A	A-	Swire Pacific Ltd	A1	AA-	A+
Samsung Electronics Co Ltd	A3	A	A-	Wharf Holdings Ltd	A1	AA-	A+
SK Telecom Co Ltd	A3	A	A-				
FRA (Total 54)							
Accor SA	Aaa	AAA	AAA	Natixis	Aaa	AAA	AAA
Air Liquide SA	Aaa	AAA	AAA	Natixis (Sub)	Aaa	AAA	AAA
Alcatel-Lucent/France	Aaa	AAA	AAA	Pernod-Ricard SA	Aaa	AAA	AAA
Alstom SA	Aaa	AAA	AAA	Peugeot SA	Aaa	AAA	AAA
AXA SA	Aaa	AAA	AAA	PPR	Aaa	AAA	AAA
AXA SA (Sub)	Aaa	AAA	AAA	Publicis Groupe SA	Aaa	AAA	AAA
BNP Paribas SA	Aaa	AAA	AAA	Rallye SA	Aaa	AAA	AAA
BNP Paribas SA (Sub)	Aaa	AAA	AAA	Renault SA	Aaa	AAA	AAA
Bouygues SA	Aaa	AAA	AAA	Rhodia SA	Aaa	AAA	AAA

(To be continued on the next page)

Appendix 1. CDS reference entity (To continue)

Cap Gemini SA	Aaa	AAA	AAA	Sanofi	Aaa	AAA	AAA
Carrefour SA	Aaa	AAA	AAA	Schneider Electric SA	Aaa	AAA	AAA
Casino Guichard Perrachon SA	Aaa	AAA	AAA	SCOR SE	Aaa	AAA	AAA
Cie de St-Gobain	Aaa	AAA	AAA	SCOR SE (Sub)	Aaa	AAA	AAA
Credit Agricole SA	Aaa	AAA	AAA	Societe Generale SA	Aaa	AAA	AAA
Credit Agricole SA (Sub)	Aaa	AAA	AAA	Societe Generale SA (Sub)	Aaa	AAA	AAA
Credit Lyonnais SA	Aaa	AAA	AAA	Societe Television Francaise 1	Aaa	AAA	AAA
Credit Lyonnais SA (Sub)	Aaa	AAA	AAA	Sodexo	Aaa	AAA	AAA
Danone SA	Aaa	AAA	AAA	Suez SA	Aaa	AAA	AAA
Electricite de France SA	Aaa	AAA	AAA	Technip SA	Aaa	AAA	AAA
European Aeronautic Defence and Space Co NV	Aaa	AAA	AAA	Thales SA	Aaa	AAA	AAA
France Telecom SA	Aaa	AAA	AAA	Total SA	Aaa	AAA	AAA
GDF Suez	Aaa	AAA	AAA	Unibail-Rodamco SE	Aaa	AAA	AAA
Gecina SA	Aaa	AAA	AAA	Valeo SA	Aaa	AAA	AAA
Havas SA	Aaa	AAA	AAA	Veolia Environnement SA	Aaa	AAA	AAA
Klepierre	Aaa	AAA	AAA	Vinci SA	Aaa	AAA	AAA
Lafarge SA	Aaa	AAA	AAA	Vivendi SA	Aaa	AAA	AAA
LVMH Moet Hennessy Louis Vuitton SA	Aaa	AAA	AAA	Wendel SA	Aaa	AAA	AAA

GER (Total 41)

Allianz SE	Aaa	AAA	AAAu	Henkel AG & Co KGaA	Aaa	AAA	AAAu
Allianz SE (Sub)	Aaa	AAA	AAAu	IKB Deutsche Industriebank AG	Aaa	AAA	AAAu
BASF SE	Aaa	AAA	AAAu	Lanxess AG	Aaa	AAA	AAAu
Bayer AG	Aaa	AAA	AAAu	Linde AG	Aaa	AAA	AAAu
Bayerische Motoren Werke AG	Aaa	AAA	AAAu	MAN SE	Aaa	AAA	AAAu
Commerzbank AG	Aaa	AAA	AAAu	Merck KGaA	Aaa	AAA	AAAu
Commerzbank AG (Sub)	Aaa	AAA	AAAu	Metro AG	Aaa	AAA	AAAu
Continental AG	Aaa	AAA	AAAu	Muenchener Rueckversicherungs AG	Aaa	AAA	AAAu
Daimler AG	Aaa	AAA	AAAu	Muenchener Rueckversicherungs AG (Sub)	Aaa	AAA	AAAu
Deutsche Bank AG	Aaa	AAA	AAAu	Porsche Automobil Holding SE	Aaa	AAA	AAAu
Deutsche Bank AG (Sub)	Aaa	AAA	AAAu	ProSiebenSat.1 Media AG	Aaa	AAA	AAAu
Deutsche Lufthansa AG	Aaa	AAA	AAAu	Rheinmetall AG	Aaa	AAA	AAAu
Deutsche Post AG	Aaa	AAA	AAAu	RWE AG	Aaa	AAA	AAAu
Deutsche Telekom AG	Aaa	AAA	AAAu	Siemens AG	Aaa	AAA	AAAu
E.ON SE	Aaa	AAA	AAAu	Suedzucker AG	Aaa	AAA	AAAu
EnBW Energie Baden-Wuerttemberg AG	Aaa	AAA	AAAu	ThyssenKrupp AG	Aaa	AAA	AAAu
Evonik Degussa GmbH	Aaa	AAA	AAAu	TUI AG	Aaa	AAA	AAAu
Fresenius SE & Co KGaA	Aaa	AAA	AAAu	UniCredit Bank AG	Aaa	AAA	AAAu
Hannover Rueckversicherung AG	Aaa	AAA	AAAu	UniCredit Bank AG (Sub)	Aaa	AAA	AAAu
Hannover Rueckversicherung AG (Sub)	Aaa	AAA	AAAu	Volkswagen AG	Aaa	AAA	AAAu
HeidelbergCement AG	Aaa	AAA	AAAu				